Patterns of Industry Agglomeration in North Carolina
1997 to 2017

Adapted from: hutton.web.unc.edu

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April 17, 2020

A paper submitted to the faculty of The University of North Carolina at Chapel Hill
in partial fulfillment of the requirements for the degree Master of City and Regional Planning.

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Overview and Introduction

In economic geography, agglomeration is the tendency for firms and individuals to collocate based on common characteristics. Across cities and regions, evidence of this tendency is readily available. From the Meatpacking District in New York City to the automotive industry in the Midwest, theorists have long held that these spatial patterns are caused by decreases in transportation costs, shared labor pools, and knowledge spillovers.

However, more recent patterns of spatial and economic growth—automation and globalization—as well as dramatic advances in communication technologies potentially push back on these long-held assumptions. According to recent work by Edward Glaeser and George Ellison (2010), measures of agglomeration have remained relatively consistent despite technological change.

To offer a more nuanced look at this tension, this project seeks to first determine trends of agglomeration across time and varying levels of geography before questioning what forces are driving these trends and whom they are affecting. Given available data sources, these analyses will consider the North Carolina context.

This submission has been adapted from the project's website. Animated and interactive visualizations can be found at hutton.web.unc.edu.

Literature Review

Theories of agglomeration date back to Smith (1776) and are key tenants of urban economics and global capitalism. Most widely attributed to Marshall (1890), the formalization of agglomeration theory has tended to assemble its causal forces under three main subgroups. First, customer-supplier interactions are thought to encourage collocation. Firms that are linked through supply chains reduce transportation costs by choosing to locate in close proximity. Second, agglomeration is believed to occur based on access to shared or common labor pools, where firm-level efficiencies are gained through access to larger networks of uniquely skilled workers. Third, collocation can facilitate the transfer of knowledge and technology between firms, catalyzing innovation and geographic specialization.

Many now-classic studies have examined these individual forces in great detail: Helsley and Strange (1990), Porter (1990), Saxenian (1994), and Audretsch and Feldman (1996). And in each case, research finds evidence that supports their existence. Throughout the literature, these three forces are still widely referenced and accepted to be true. In terms of effects, agglomeration facilitates efficiencies and allows firms to distribute their products to larger markets. Productivity gains encourage specialization and allow competition with the global market. Increased productivity is then translated to higher wages (Duranton and Kerr, 2018). At the same time, however, either as a result (Storper, 2013) or cause (Glaeser, 2010), population growth occurs as firm density increases, leading at some point to theoretical diseconomies of scale. Population growth in turn causes increased housing and transportation costs by bidding up the cost of land, while it also creates negative environmental externalities (Duranton and Kerr, 2018; Puga, 2010).

Measures of Agglomeration

While theoretical models of agglomeration have been exhaustively studied, many contemporary authors claim that empirical studies have not kept pace. Early studies focused on “wage premiums paid to urban workers” in identifying agglomeration but had very little practical policy implications, failing to identify the mechanisms and specific industries through which agglomeration occurred (Duranton and Kerr, 2018).

The relatively recent rise of large establishment-level data sets, however, has provided a platform to better measure and understand the driving forces of agglomeration economies. Additionally, beyond new mechanisms to simply measure agglomeration, these large data sets have allowed estimations of spillover lifecycles (Rosenthal and Strange, 2004), mechanisms of firm selection and productivity (Combes et al., 2012), and more dynamic analyses of firm entry and exit (Klepper, 2010).

The most widely used measure of agglomeration itself is an index developed by Ellison and Glaeser (1997). Using firm-level data, their index controls for randomness in firm location and size, incorporating Herfindahl coefficients to identify industries concentrated in a small number of individual firms. Typically used over existing regional geographies (counties and states), the relative ease of calculation has made the Ellison Glaeser Index a popular choice in contemporary regional economic literature.

Ellison Glaeser Index of Agglomeration

$$\gamma \equiv \frac{\sum_{i=1}^{M} (s_i - x_i)^2 - \left(1 - \sum_i x_i^2\right) \sum_k z_k^2}{\left(1 - \sum_i x_i^2\right)\left(1 - \sum_k z_k^2\right)} = \frac{\sum_{i=1}^{M} (s_i - x_i)^2 - \left(1 - \sum_i x_i^2\right) H}{\left(1 - \sum_i x_i^2\right)(1 - H)}$$

In response to Ellison and Glaeser (1997), Duranton and Overman (2005) point to two major deficiencies. First is the inability to measure for statistical significance. Second is the boundary limitations caused by polygonal geography. Firms that are clustered across boundaries (such as across county or state lines) might not be accurately captured. Instead, they propose a point- and distance-based measure that considers the entire distribution of pairwise distances, using a k-means clustering algorithm.

Their specific study finds that nearly half of all 4-digit industries in the United Kingdom are agglomerated and that clustering occurs at distances of less than 50 kilometers. The sophistication of the Duranton and Overman measurement, however, is computationally intense, making its calculation much more difficult. For this reason, the Ellison Glaeser method appears to remain the preferred.

Finally, as discussed briefly above, measures that consider wage premiums and land rents have also been proposed (Glaeser and Mare, 2001). However, this approach seems to run into several confounding variables, including not least income inequality and spatial segregation, and is perhaps best suited for analyses of population rather than firm agglomeration.

Geography of Agglomeration

The consideration of cluster shape and size is an area that requires more research. The size of individual clusters and their associated geographies of agglomeration appear to be determined based on the reason for which the cluster emerged. Going back to the original theories proposed by Marshall, knowledge- and technology-based clusters are typically smaller than those caused by labor-pooling and industry linkages. Furthermore, cluster geography appears to be larger than labor pooling would suggest alone. While commuting patterns tend to extend 20 miles or less, for example, agglomerations based on shared labor resources appear to stretch much further (Duranton and Kerr, 2018).

One model by Kerr and Kmoiners (2015) envisions small, overlapping regions, where firms interact within their own boundaries. The radius from each firm is a curve of declining benefit, illustrating that the benefits of agglomeration decline with distance. This curve is known as the maximal spillover radius and was empirically measured for different technologies based on the relative distance of patent citations. While some technologies, such as semiconductors, have very short radii, others appear to be much larger. Overall, this work suggests the need for more dynamic geographies in measuring levels of agglomeration.

Similarly, Feser (2000) shows that Ellison and Glaeser's original measure is not robust against changes in geography. Using both zip codes and counties to recreate the index in Tennessee and North Carolina, Feser found statistically significant differences by level of geography and suggests that sensitivity should be tested before further analyses of concentration are undertaken. Finally, Holmes and Sanghoon (2010) use six by six-mile grids to study patterns in population distribution and density across the United States. This simulated unit of geography was found to be robust when compared to smaller and greater units while also allowing for a standardized approach. Glaeser (2010) notes that a similar method of analysis could be useful in measuring industrial agglomeration. Both the size and consistency of these geographies make this particularly true for studies seeking to understand patterns of change over time.

Measuring the Causes of Agglomeration

Although the literature points to clear beneficial externalities of agglomeration, very little empirical evidence has been offered on what forces are driving firm clusters. Identification of these forces is important in developing more concrete industrial policy (Howard et al., 2016). Ellison et al. (2010) point out that the main difficulty in determining what causes agglomeration is that the result of each force is the same.

Either because of knowledge transfers or labor pooling, the outcome is some measure of firm agglomeration. Nevertheless, the results from Ellison et al (2010) show that input-output linkages and labor needs are most strongly correlated, while technological and knowledge spillovers appear to be the weakest factor in predicting industry clusters. Interestingly, their findings further suggest that the cumulative effect of the three Marchallian factors are more important than any single one.

Finally, Howard et al. (2016) measured collocation of firms at different levels of geography in Vietnam, seeking to improve the Ellison et al. methodology. Critically, they found that at the smallest level of geography, collocation is not determined by cost savings. Meanwhile, across all geographies, value chain relationships are predictive of collocation and may be motivated by technology transfers (as Porter suggests). The strength of technology transfers as a motivating factor, however, decreases as geography size increases.

Methodology

Based on the review of existing literature, a methodological framework which seeks to illuminate spatial and temporal trends in agglomeration, as well as their causal forces, has been constructed. The following sections will review this methodology as well as the steps taken in its construction.

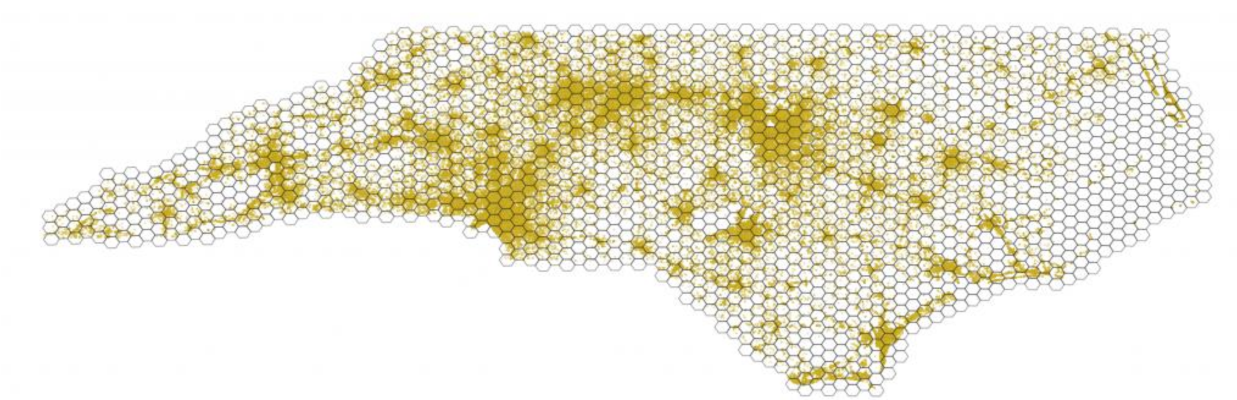
Measuring Agglomeration

First, measures of agglomeration were tested across varying levels of geography. Work by Ellison and Glaeser has established a widely accepted index of agglomeration, and work by Feser has confirmed differences in its sensitivity at different scales of geography. Both studies, however, relied on preexisting geographies (counties and zip codes) in their calculations. This is problematic given the varying size and shifting nature of legal boundaries.

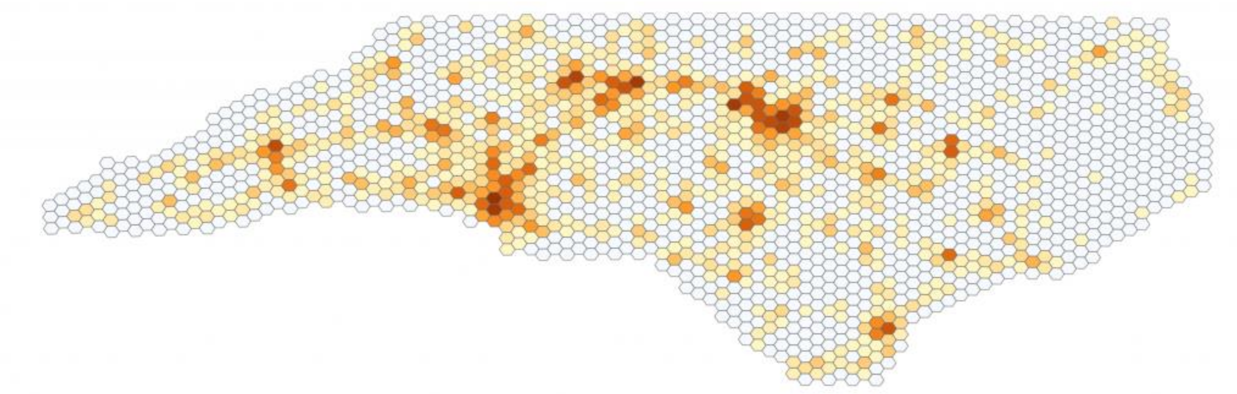
Geocoded firm-level data from **Reference USA** offers the opportunity to extend this work by creating uniform geographies across time and space, allowing consistency in measures of change and potentially offering insight into the importance of scale in firm clustering.

The figures below display this independent grid geography for North Carolina. The first plots individual establishments (in 2017) across the state, while the second assigns establishment-level employment to the individual grid polygons, offering a clearer picture of overall employment distribution.

Geocoded and Plotted Establishments (2017)



Establishment Employment Joined to Independent Geography (2017)



Once joined to the independent polygons, the Ellison-Glaeser Index of Agglomeration was calculated for each industry sector for each year from 1997 to 2017. Specifically, this was accomplished through two key packages in R. The first, **Spatial Features**, allowed a loop to spatially join each year of firm data to the constructed polygons, while the second, **Regional Economic Analysis Toolbox,** facilitated the calculation of the Ellison-Glaeser Index. Results for three- and four-digit NAICS levels are displayed on the **Index of Agglomeration** page.

Interpreting Correlations

Based on the key theoretical assumption that technological adoption decreases transportation costs and therefore facilitates firms in the process of deagglomerating, the Bureau of Economic Analysis's (BEA) commodity and industry use tables were utilized to determine each three-digit NAICS sector's expenditure on technological inputs relative to industry output. Calculations were made for both 1997 and 2017, which change in relative technological spending was also identified. Input industries and commodities identified as contributing to technological adoption are identified below.

- 334: Computers and Electronic Products
- 514: Data Processing, Internet Publishing, and Other Information Services
- 5415: Computer Systems Design and Related Services.

Similarly, using BEA data, industry productivity was measured by each sector's total output relative to the total hours worked by both full- and part-time employees in that sector. These calculations were made for both 1997 and 2017.

Importantly, both of the above constructed measures rely on national data and therefore do not reflect the idiosyncrasies of North Carolina firms. Nevertheless, given the unavailability of state-level data as well as each measure's relative nature, they serve as adequate proxies by which to interpret potential correlations.

To understand the relationship between agglomeration and industry average wages, wage quotients were calculated using both 1997 and 2017 editions of the North Carolina Quarterly Census of Employment and Wages. In this case wage quotient refers to each industry's annual average wage relative to the state's overall annual average wage. Thus, any quotient above one indicates an industry for which wages are higher than the state's average.

The results of each of these potential correlating variables as well as further methodological discussions can be found on the **Interpreting Correlations** page.

Index of Agglomeration

With establishment employment joined to the independent geography, calculation of the Ellison-Glaeser Index can be conducted. The table below shows these results at the four-digit NAICS level, displaying the most highly agglomerated sectors relative to the results from the county-level calculation. In line with Feser's (2000) findings, the relative disparity between grid- and county-level results confirm that the index is sensitive to geographic scale.

While Residential Mental Health Facilities (NAICS 6232) is the most highly agglomerated industry sector in both the county- and grid-level calculations, the majority of industries listed fall under manufacturing. Highly specialized sectors such as Computer and Peripheral Equipment Manufacturing (3341), Pharmaceutical and Medicine Manufacturing (3254), and Semiconductor and Electronic Component Manufacturing (3344) are all relatively agglomerated in North Carolina.

Agglomeration Index Results for Grid and County Geographies, 2017

Industry	Grid Index	County Index
6232: Residential Mental Health Facilities	0.386	3.830
3341: Computer and Peripheral Equipment Manufacturing	0.132	0.210
3254: Pharmaceutical and Medicine Manufacturing	0.127	0.220
3116: Animal Slaughtering and Processing	0.074	0.180
3344: Semiconductor and Electronic Component Manufacturing	0.066	0.055
4811: Scheduled Air Transportation	0.051	0.043
6113: Colleges and Universities	0.049	0.055
3359: Other Electrical Equipment and Component Manufacturing	0.044	0.010
5511: Management of Companies and Enterprises	0.042	-0.001
3371: Household and Institutional Furniture Manufacturing	0.030	0.103

From 1997 to 2017, nearly every industry has experienced a change in its measure of agglomeration. While these changes are discussed with more nuance on the **Temporal Patterns** page, more high-level information is provided below.

This table shows all industry sectors that experienced an increase in EGI of at least 0.005 over the 1997 to 2017 time period. These agglomerating sectors are characterized by relatively high annual wages, offering a weighted average salary of nearly $75,000. Furthermore, these sectors represent large employment bases for the state, with 11 of the 15 employing more than 10,000 individuals in 2017. Finally, there is again a disproportionate representation of manufacturing sectors, which are perhaps increasing in relative density as overall employment falls.

Together these patterns suggest that large and high-paying industries are clustering in increasingly tighter areas of the state. For North Carolina, understanding the unique **Spatial Patterns** of each sector will be critical in future economic development planning.

Agglomerating Industries, 1997 to 2017

Industry Description	Change in EGI	EGI 2017	Employment 2017	Average Wage 2017
Broadcasting, except internet	0.09	0.096	7,795	$74,910
Management of companies and enterprises	0.07	0.042	82,854	$108,032
Mining, except oil and gas	0.04	0.042	2,626	$63,050
Computer and electronic product manufacturing	0.03	0.031	32,413	$114,810
Textile product mills	0.02	0.023	6,221	$36,116
Electrical equipment and appliance mfg.	0.02	0.020	21,793	$65,800
Food manufacturing	0.02	0.018	56,024	$39,742
Performing arts and spectator sports	0.02	0.011	15,379	$75,621
Nonstore retailers	0.02	0.012	13,292	$42,721
Animal production and aquaculture	0.01	0.020	8,712	$37,301
Chemical manufacturing	0.01	0.016	41,258	$85,999
Furniture and related product manufacturing	0.01	0.034	36,748	$38,275
Transportation equipment manufacturing	0.01	0.007	35,614	$64,301
Support activities for transportation	0.01	0.012	15,711	$49,077
Electronic markets and agents and brokers	0.01	0.004	32,082	$95,137

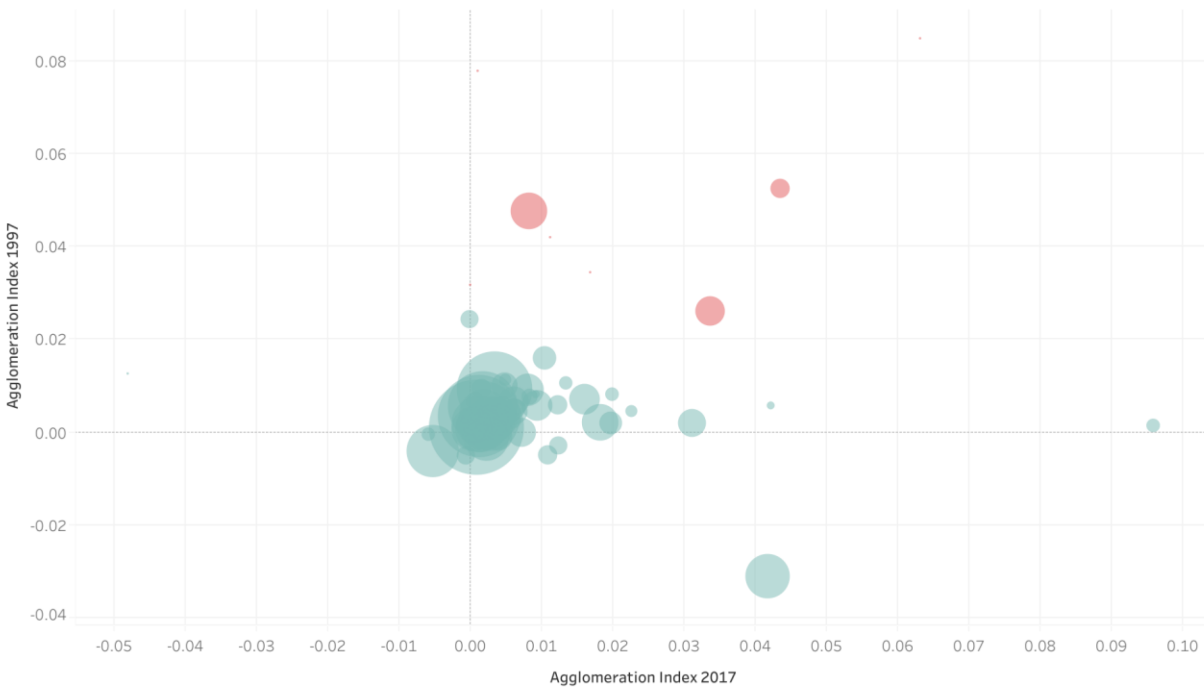
Similar to the agglomerating sectors above, deagglomerating industries are characterized by relatively high wages, offering a weighted average annual salary of $77,000. However, unlike those industries moving toward higher levels of agglomeration, these industries are generally smaller, with just 8 of the 16 employing more than 10,000 individuals in 2017. In terms of the types of industries represented, many fall under transportation and warehousing, which is perhaps a product of e-commerce and the rise of widespread distribution.

Deagglomerating Industries, 1997 to 2017

Industry Description	Change in EGI	EGI 2017	Employment 2017	Average Wage 2017
Lessors of nonfinancial intangible assets	-0.08	0.001	430	$77,851
Water transportation	-0.06	-0.048	211	$38,662
Insurance carriers and related activities	-0.04	0.008	56,260	$77,544
Fishing, hunting and trapping	-0.03	0.000	28	$44,369
Scenic and sightseeing transportation	-0.03	0.011	368	$24,326
Data processing, hosting and related services	-0.02	0.000	13,825	$101,334
Funds, trusts, and other financial vehicles	-0.02	0.063	82	$484,979
Pipeline transportation	-0.02	0.017	334	$87,983
Air transportation	-0.01	0.043	15,229	$73,983
Electronics and appliance stores	-0.01	0.002	14,270	$42,533
Transit and ground passenger transportation	-0.01	0.005	6,016	$31,486
Beverage and tobacco product manufacturing	-0.01	0.001	11,214	$57,281
Professional and technical services	-0.01	0.003	239,321	$79,495
Primary metal manufacturing	-0.01	-0.006	7,507	$64,112
Securities, commodity contracts, investments	-0.01	0.010	23,282	$142,001
Warehousing and storage	-0.01	0.005	28,380	$39,863

Finally, the below bubble chart compares measures of EGI for 1997 and 2017. The size of each bubble corresponds to industry employment in North Carolina in 2017. Cluster analysis reveals two distinct sets of industries. Identified in red, the first cluster consists of Air Transportation, Insurance Carriers and Related Activities, Furniture and Related Product Manufacturing, and several smaller sectors. Despite change over time, these industries are generally agglomerated in both years.

Identified Clusters of Agglomeration, 1997 and 2017



Interpreting Correlations

Based on the available **literature**, this section seeks to understand the corresponding characteristics of agglomeration. In particular, brief discussions on the relationship between agglomeration and labor productivity, average wage, and technological adoption will be reviewed. More specific methodologies are discussed in the **Methodology** section.

Log Transformations

For many of the below models, logarithmic transformations have been used to normalize the distribution of the independent and/or dependent variables. This process is common when data are skewed and allows the preservation of linear model. For each of the transformations, a log base 10 was used.

In interpreting the relationship between independent and dependent variables, it is necessary to keep in mind the logarithmic transformations. For each of the below categories, I have contextualized the results as “a 100% increase in X results in a __% increase in Y.” These statements account for the logarithmic transformations.

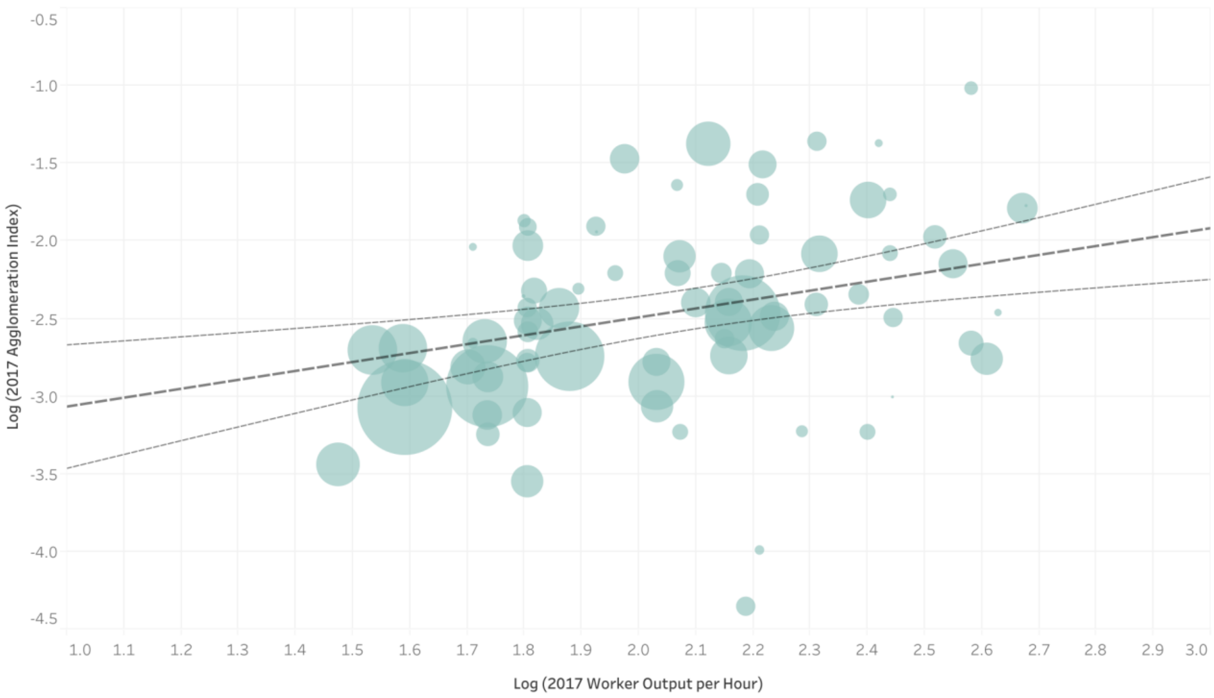
Labor Productivity

This analysis shows a clear correlation between labor productivity and agglomeration. That is, industry sectors that produce higher levels of output per employee-hour are more likely to be agglomerated. When both labor productivity and EGI are transformed to logarithmic scales, an R-Squared value of 0.13 and a P-value of 0.001 are achieved. The logarithmic correlation is 0.57.

Nevertheless, when these results are normalized, the directional relationship between productivity and agglomeration is extremely inelastic. An industry sector that increases productivity by 100% is likely to see an increase in agglomeration of just 0.02%.

Importantly, the direction of this particular relationship is critically important. Rather than a dependent agglomeration variable, one could just as easily argue that labor productivity improves as industries and firms cluster. Though difficult to prove without firm-level and time-series productivity data, this finding would align with the available literature. Access to shared labor pools, decreased transportation costs, and an exchange of industry knowledge all increase productivity and are all facilitated by spatial proximity.

Agglomeration by Labor Productivity, 2017



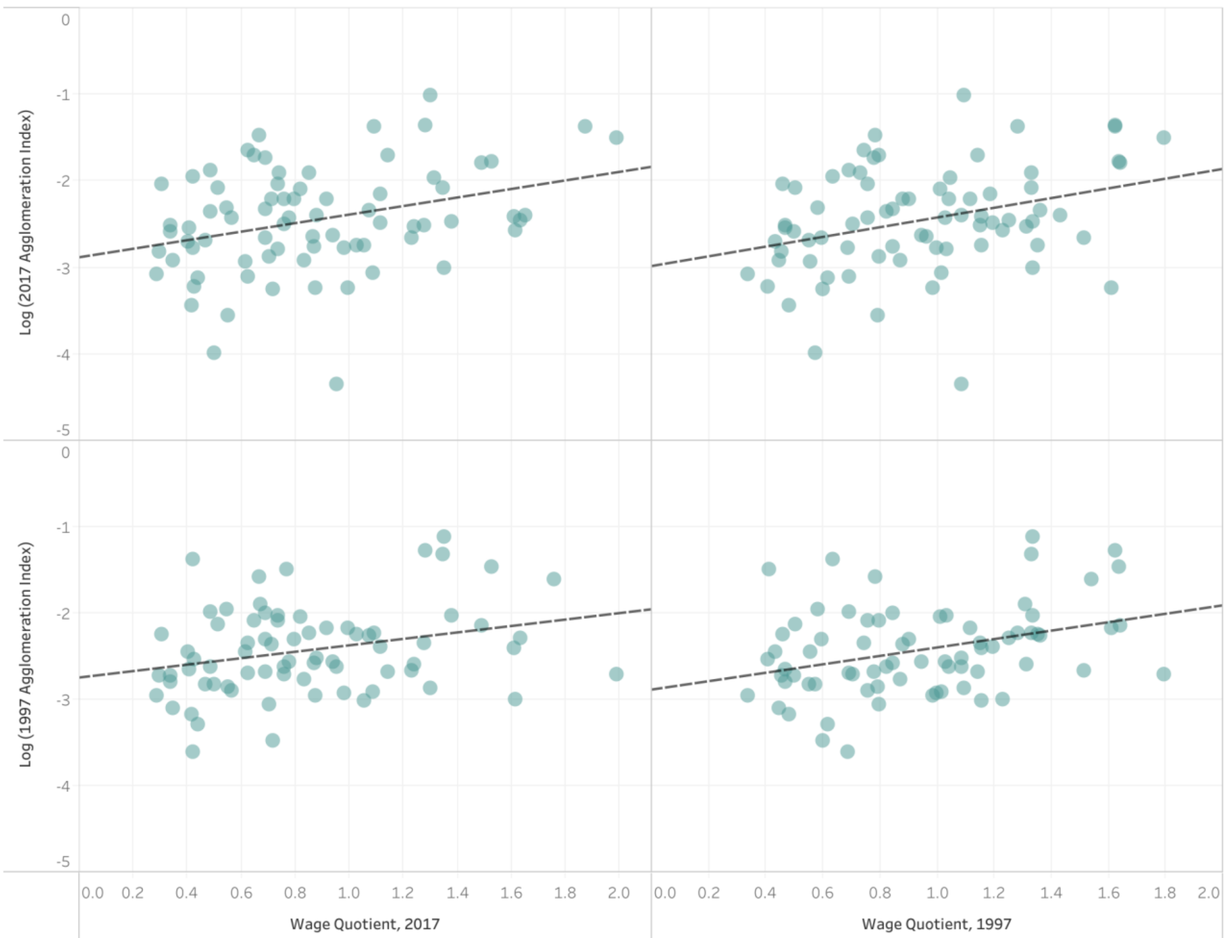
Relative Wage

Similar to labor productivity, there appears to be some relationship between relative average wage and industry agglomeration. Here, I present a wage quotient for 1997 and 2017. For each year, industry average wages are compared to the overall average wage in North Carolina. A quotient of one, for example, indicates perfect parity with the overall average. Each of the wage quotients are compared to agglomeration measures from 1997 and 2017. The EGI for each year has been transformed using the LOG method, while the wage quotients remained unchanged.

Interestingly, while each of the four comparisons shows a positive correlation, that between the 1997 wage quotient and 2017 agglomeration measure appears to be the strongest. This perhaps suggests while higher wages are characteristic of agglomerated industries, they are also predictive of future agglomeration.

In the 1997 wage quotient and log-transformed 2017 agglomeration measure correlation, the regression model achieves an R-Square value of 0.11, a P-value of 0.003, and a correlation coefficient of 0.56. When normalized, these results indicate that a 100% increase in the 1997 wage quotient is likely to lead to a 0.37% increase in the 2017 agglomeration measure.

Agglomeration by Relative Average Wage, 1997 and 2017



Adoption of Technology

The final correlation analysis examines the relationship between technology expenditure and change in agglomeration. According to the most widely available literature, technology adoption should reduce transportation and communication costs, facilitate remote work, and reduce the need for firm proximity. In essence, technology adoption should lead to industry deagglomeration. To test this theory, relative industry-wide expenditures of technology-oriented commodities or inputs were used as a proxy for technology adoption.

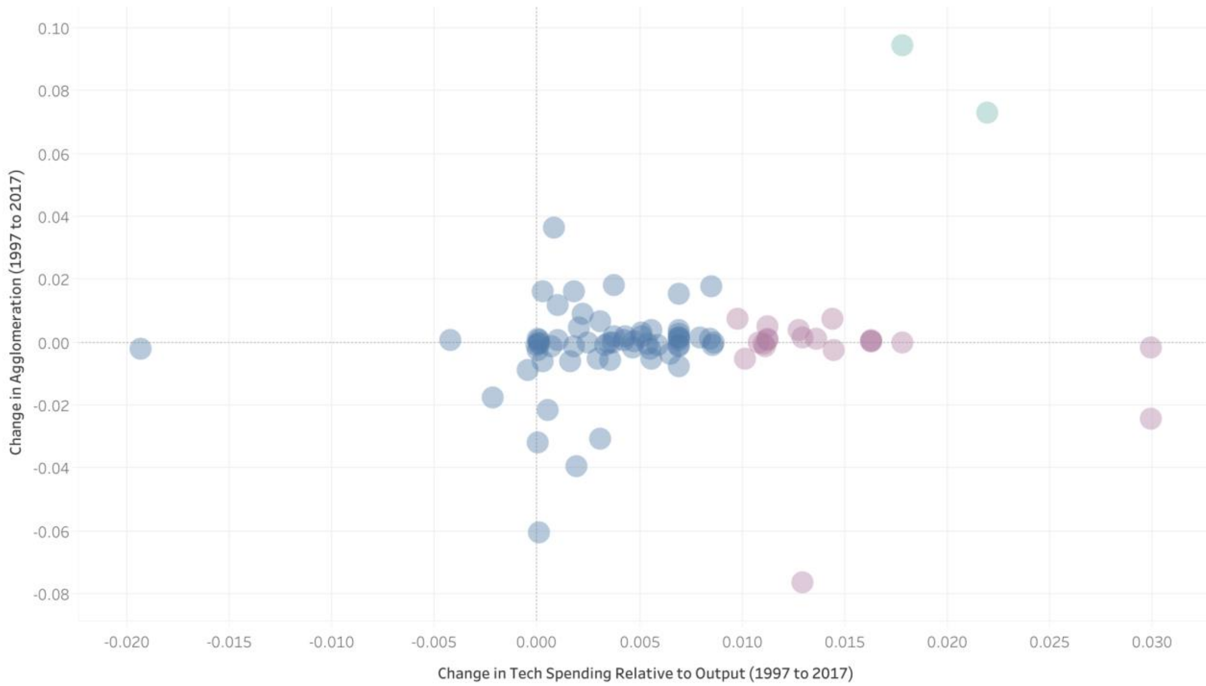
Relative technological expenditures for 1997 and 2017 were modeled against change in EGI over the same time period. Rather than a decline in agglomeration, the model shows an overall increase in agglomeration for highly technologically dependent industries. This finding contradicts traditional theoretical understandings of agglomeration as well as more recent findings by Ellison, Glaeser, and Kerr (2010) ,which show temporal patterns of agglomeration to be relatively consistent across industries.

The below charts show that while relative technology expenditures have increased since 1997, the correlation coefficient between expenditures and change in agglomeration is higher for the 1997 model. With an R-Squared value of 0.10 and P-value of 0.003, the model shows that a 100% increase in relative technology expenditures in 1997 would lead to a 58% increase in agglomeration by 2017.

Change in Agglomeration by Relative Technology Expenditure, 1997 and 2017

While these findings are statistically significant, it is important to note that the positive correlation is driven by two primary outliers. Identified below as Cluster Three, Management of Companies and Broadcasting are two industry sectors which have both seen increases in relative technology expenditure and measures of agglomeration. Without these two industry sectors, the model would likely show no relationship.

Change in Agglomeration by Change in Relative Technology Expenditure, 1997 to 2017

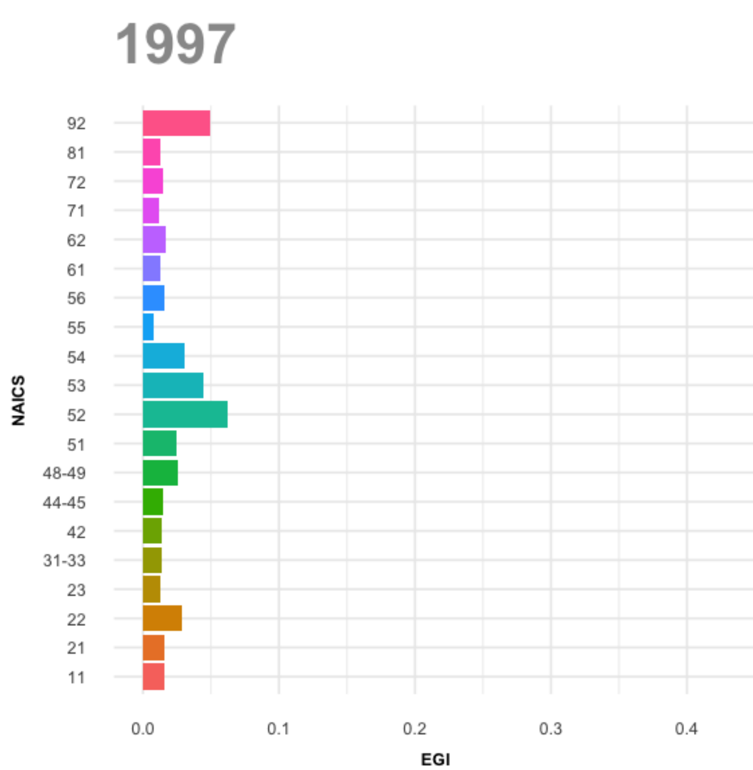


Temporal Patterns

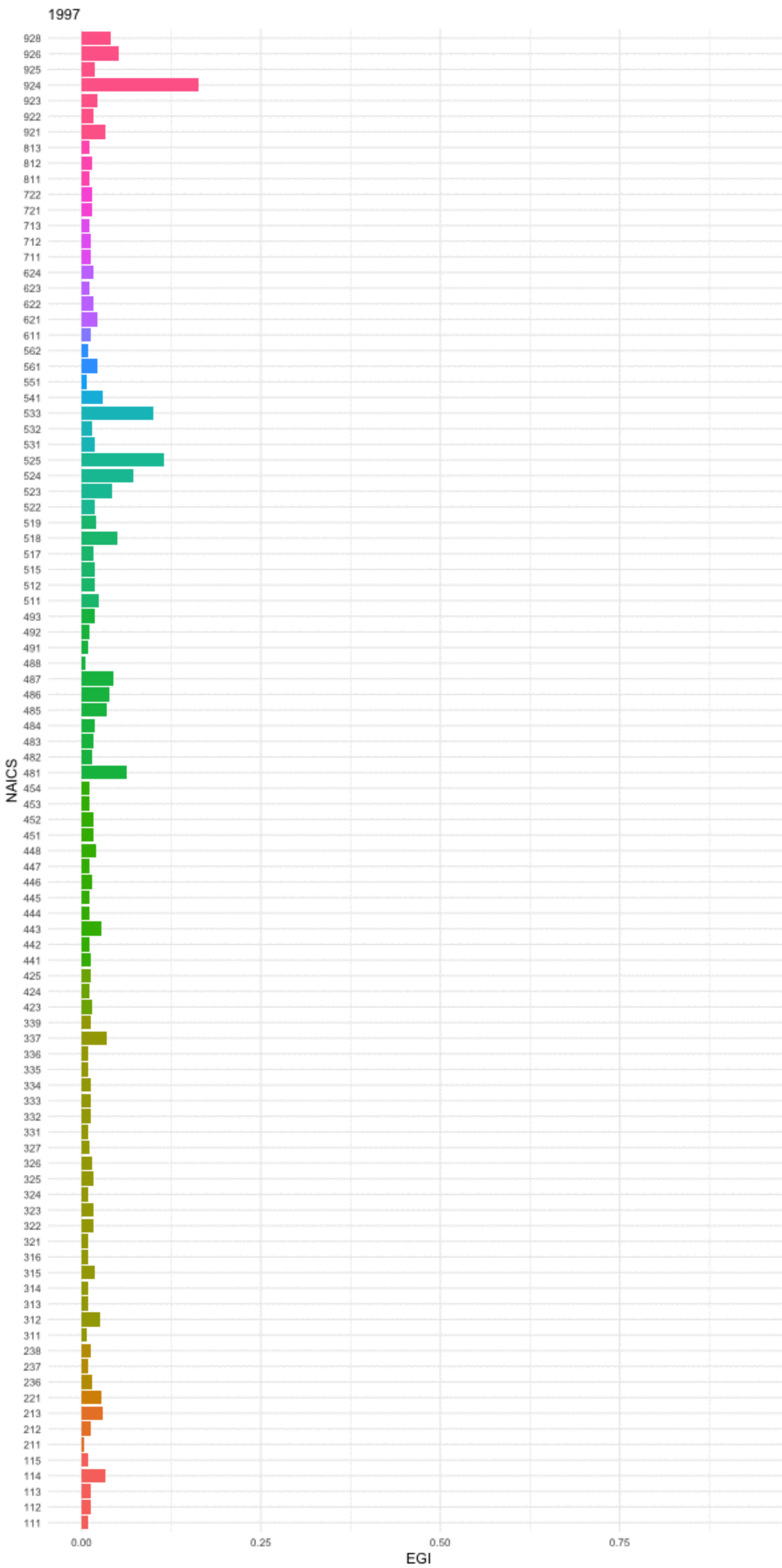
In reviewing annual measures of agglomeration for Two- and Three-Digit NAICS codes, potential problems with either the Ellison-Glaeser methodology or available firm-level data emerge. The below chart shows agglomeration measures for each year for each two-digit industry sector. Rather than smooth transitions toward long-term agglomeration or deagglomeration, each industry is characterized by dramatic fluctuations. While the two-digit chart is presented first for ease, the more detailed three-digit chart is also presented below.

Overall, year-over-year changes follow no long-term patterns. This is particularly true for Management of Companies industry sector (55), which shifts most dramatically between years. While I had hoped this section would reveal more nuanced patterns over time and between industry sectors, it has instead opened more lines of inquiry. Most importantly, it potentially calls into question the validity of previous corollary analyses and EGI methodology. Additional analysis beyond the scope of this project is necessary.

Ellison-Glaeser Index by Two-Digit NAICS, 1997 to 2017 (GIF Still)



Ellison-Glaeser Index by Three-Digit NAICS, 1997 to 2017 (GIF Still)

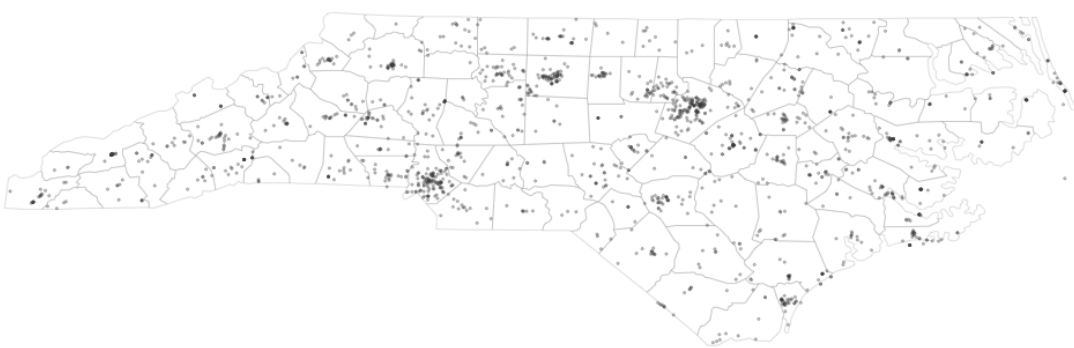


Spatial Patterns

Given the variability in agglomeration over time, I have conducted spatial analysis of individual firms. The maps below highlight individual establishments that (1) remained open and operational and (2) moved from their original locations during the 1997 to 2017 time frame. While this section does not add to the agglomeration research per se, it offers some complementary insight into where firms are choosing to locate.

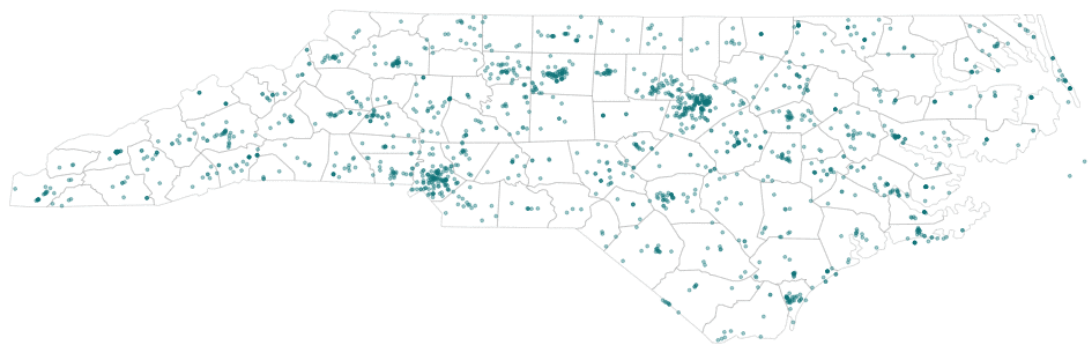
The first map below shows all industry sectors. Notice that while many establishments are moving relatively large distances across the state, the vast majority are simply suburbanizing. They are moving not only from the central cities but also from the more rural periphery, and they are forming new, more dispersed clusters of density in suburban areas.

All Industry Sector Establishments, 1997 to 2017 (GIF Still)



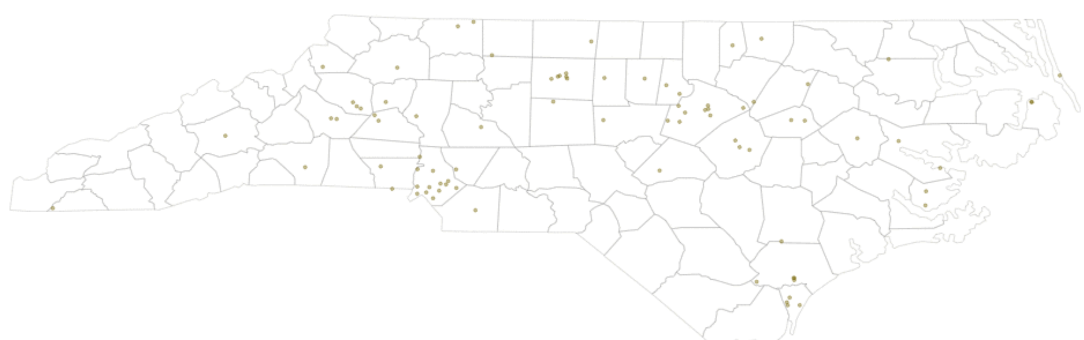
Focusing only on the information, finance, and management sectors (NAICS 51 to 56), a similar pattern is revealed. Establishments are suburbanizing, yet there appears to be more obvious clustering in the Charlotte and Research Triangle regions. Firms are moving from outside these areas, relocating to the state's major population centers and further solidifying the dominance of these regions in professional services.

Information, Management, and Finance Sector Establishments, 1997 to 2017 (GIF Still)



Unfortunately, when the same analysis is completed for manufacturing sectors (NAICS 31-33), not enough establishments have remained open or moved during the 1997 to 2017 time frame for any meaningful interpretation to take place.

Manufacturing Sector Establishments, 1997 to 2017 (GIF Still)



Planning and Policy Implications

Overall, this project has sought to test temporal and spatial patterns of industry agglomeration against the conventional literature. Where scholars have long held that firms collocate to decrease transportation costs and share labor markets, the analyses provided here have only partially confirmed these assumptions. By examining annual, geolocated establishment-level data from 1997 to 2017, this project has revealed details that had previously been uncovered. For economic development professionals and policymakers in North Carolina and across the country, these patterns can help shed light on the spatial components of inequality and regional development.

Agglomeration is intrinsically linked to regional labor markets. In both measures of productivity and relative wage, agglomerating industries were found to be positively correlated. From a policy perspective, this means that well-paying and highly productive industries are spatially concentrated, isolated to educated urban areas. In North Carolina, this is occurring most dramatically in the Research Triangle and Charlotte regions, areas of the state that have traditionally offered higher wages and higher quality employment. Wealthy areas will continue to become wealthier, as industries dependent on specialized labor markers are drawn by agglomerative forces.

Technology adoption has not precipitated industry dispersion. Rather than allow industries to locate to cheaper areas of the state, technology has had either positive or no effects on agglomeration. For the most part, industry sectors which rely more heavily on technology inputs show no corresponding change (either positively or negatively) in agglomeration. Two outlying industry sectors, Broadcasting and Management, are exceptions. They have become more agglomerated as they have spent larger portions of their total inputs on technology. While transportation costs and labor markets are seen as the two conventional drivers of agglomeration, this finding shows that technology does not overcome the basic need for proximity. Firms are tied to their geographies, and advances in technology have so far been unsuccessful in untethering workers from the spatial constraints of labor.

Both of the previous points speak to the urban-rural divide in North Carolina. The loss of manufacturing in the state's rural periphery has occurred as professional and financial service sectors grow in the state's urban areas. Reliance on a well-educated labor force encourages regional agglomeration. As a result, the state's two largest urban areas have experienced growth in employment and wages while small communities across the state have continued to decline. For state policymakers, these patterns help explain the urban-rural divergence and show that education and a skilled labor force are critical for economic growth.

Throughout the state, firms are concentrating around suburban nodes. Throughout North Carolina, firms have moved out from the urban core, while more rural establishments have moved inward. In both cases, firms are relocating in polycentric nodes around the state's largest metros. In effect, employment is both decentralizing and clustering. For planners, this obviously affects infrastructure development and commuting patterns, but it also affects economic development, further isolating employment and exacerbating spatial mismatch.

Fluctuations in year-over-year measures of agglomeration raise methodological concerns. Unfortunately, when evaluated on an annual basis, temporal patterns of the Ellison-Glaeser Index of Agglomeration show signs of inconsistency, with high degrees of variability between years. Further research is needed to evaluate the measure's efficacy, and future projects might look to the pairwise methodology developed by Duranton and Overman. Though more computationally intense, this method may more accurately measure temporal patterns of agglomeration.

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